# FINGERPRINTING SOILS – A PROOF OF CONCEPT

A Senior Scholars Thesis

by

CATHERINE KOBYLINSKI

Submitted to the Office of Undergraduate Research
Texas A&M University
in partial fulfillment of the requirements for the designation as

UNDERGRADUATE RESEARCH SCHOLAR

April 2011

Major: Bioenvironmental Sciences

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Approved by:

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| Research Advisor: | Cristine Morgan |
| Director for Honors and Undergraduate Research: | Sumana Datta |

April 2011

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# ABSTRACT

Fingerprinting Soils - A Proof of Concept.
(April 2011)

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Forensic soil characterization is an under-explored field in the forensic sciences. One aspect of forensic sciences is Locard's Exchange Principle, which states that every contact leaves a trace. As soil characterization technology improves, applications of soil forensics can more accurately identify if a soil sample collected from a suspect corresponds to samples collected at a crime scene. This research focuses on the use of visible near and infrared, diffuse reflectance spectroscopy (VNIR DRS) to develop spectral "fingerprints" of soils. Our hypothesis is that VNIR spectra of soils from a crime scene are unique from other soils, even soils of the same soil series. If soil spectra from a crime scene are unique, this data can be used to accurately assess Locard's Exchange Principle. Soil samples were collected within in a thirty-mile radius of a designated "crime scene" in the Brazos River floodplain near Texas A&M University. The crime scene is mapped as a Weswood silt loam (Udifluventic Haplustepts). Three other similar soil series were identified to test uniqueness of soil spectra within and between soil series. These soils included Yahola fine sandy loam (Udic Ustifluvents), Ships clay, (Chromic Hapluderts) and Silawa fine sandy loam (Thermicultic Haplustalfs). Sixteen soil samples were collected from randomly located soil mapped Weswood, and eight soil samples were collected from Ships, twelve from Yahola and ten from Silawa (n=48). At the crime scene, an X-shaped sampling geometry was constructed. At 5 m intervals along the X, surface soil samples were collected and a single sample was collected at the center of the X (n=17). The soil samples were air dried, ground to pass through a 2 mm sieve, and scanned with a VNIR spectroradiometer (350-2500 nm). Principle components analysis was performed to deduce the uniqueness of the soil spectra between the four soil series from the crime scene samples. Reflectance spectra of Yahola and Weswood soils were very similar, while Silawa and Ships were easily differentiated. The first derivative of the reflectance spectra improved differentiation between Weswood and Yahola. Spectral properties of the crime scene soils were mostly unique with X other soil samples within the range of the first three principal components of the crime scene soils. VNIR fingerprinting of soils from a particular location is a promising technique for forensic soil science.

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# CHAPTER I

# INTRODUCTION

Classical soil characterization by soil scientists are numerous and well documented; however, most soil analysis techniques were designed to identify agricultural suitability rather than for forensic application. In soil forensic applications, such as trace evidence collection, the goal is to identify a soil as being uniquely associated with a soil sample at another location, perhaps a crime scene. Soil characterization techniques include physical, chemical, and biological analysis of soil components. For example, particle size distribution, clay-sized mineralogy, identification of biota and quantifying anions and cations on exchange sites and in soil solution are typical (Dane and Topp, 2002; Dixon and Schulze, 2002; Sparks, 1996). Forensic soil analyses are similar and commonly include color, particle size distribution, and microscopic examination of soil particles to determine their shape and structure, and chemical elemental analysis (Pye, 2007). Because all of these analyses (except color) require several grams of dried ground soil, require time intensive sample pre-processing and destroy the soil sample during analysis, these procedures are limited to quantifying soil properties in cases where ample soil material and financial resources are available for analysis. In some forensic cases where only a small or trace amount of soil is available; for example a

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This thesis follows the style of the *Forensic Examiner.*

scraping from clothing or a vehicle tire, current analyses methods are not applicable. A method that uniquely identifies soils, uses small (< 5 g.) samples, requires little soil processing, and is nondestructive, could facilitate the use of soil trace evidence in forensics. Visible Near-Infrared (VNIR) diffuse reflectance spectroscopy is a method that rapidly and non-destructively measures soil reflectance continuously from 350 to 2500 nm. VNIR spectroscopy has been used in soil science to quantify soil clay content, soil chemical properties, and classify soil mineralogy (Gaffey, 1986; Shepherd and Walsh 2002; Brown et al., 2005; Waiser et al., 2007; Morgan et al., 2009). The aim of this research is to explore the applicability of VNIR spectroscopy as a soil fingerprinting method for use in forensic soil science.

VNIR spectroscopy has been used in soil science since the late 1990's, but only recently has been used in non-research applications (e.g. soilmap.net and US soil carbon characterization). This technique provides a measure of the reflectance of soil samples as a function of wavelength. VNIR-DRS has been utilized in soil applications because of the unique reflectance and emittance spectral signatures of natural surfaces, including soil, which are sensitive to specific chemical bonds in materials, whether solid, liquid or gas. This technique has the advantage of being sensitive to both crystalline and amorphous materials, unlike some diagnostic methods, like X-ray diffraction (Clark, 1999). To date VNIR spectroscopy has been used in soil science as a method to determine the chemical makeup of a soil and measure other soil properties that can differentiate a soil. These properties include clay content, clay mineralogy, inorganic carbon, organic carbon, and cation exchange capacity (Gaffey, 1986; Ben-Dor and Banin 1995; Shepherd and Walsh 2002; Brown et al., 2005; Lagacherie et al, 2007; Waiser et al., 2007; Morgan et al., 2009). The main advantages of VNIR spectroscopy are that it requires little soil preparation (drying and grinding only), is non-destructive, and supports rapid collection and analysis of data. Once a soil is dried and ground actual collection of soil VNIR reflectance takes less than 5 seconds, and includes multiple scans. In four hours a trained operator can collect, process and analyze spectral data on approximately 50 soil samples. The primary disadvantage of the technique is that methods for analyzing the data are still being explored and developed.

In forensics, scientists analyzing soil evidence have focused on physical descriptors, clay-sized mineralogy, and biological analysis. Physical descriptors include color, particle size distribution, and microscopic examination of soil particles to determine their shape and structure (Pye, 2007). The color of soil is established using a Munsell color book, in which a scientist visually matches the color of a soil sample to a Munsell color chip of a specific hue, value, and chroma. During a VNIR spectroscopy measurement of soil, the visible spectrum (390 to 750 nm) is precisely quantified at 1-nm wavebands. Hence for color analysis, VNIR spectroscopy removes error associated with varying interpretation of soil colors by different human eyes.

Particle size distribution refers to the percentages of sand-, silt-, and clay-sized particles present within a soil. While quartz-based sand and silt particles are not directly measured by VNIR spectroscopy, absorptions by water bonds associated with clay content and other bonding associated with clay type provide information for reliable clay content prediction. Previous research on air-dried, ground soil samples has shown VNIR predictions of soil clay content with root mean squared deviation (RMSD) values ranging from 62 to 11 g $kg^{-1}$ (Ben-Dor and Banin, 1995; Janik et al., 1998, Shepherd and Walsh, 2002; Islam et al., 2003; Sorensen and Dalsgaard, 2005; Brown et al., 2006; Waiser et al., 2007). Spectroscopy-based clay predictions on dried, and ground soil samples are very similar to standard laboratory measurement errors which are 50 and 20 g $kg^{-1}$ using the hydrometer and pipette methods, respectively (Gee and Or, 2002).

Forensic soil scientists perform chemical analyses to discern the mineralogical makeup of a soil. The clay sized-fraction is composed of different types of clay sized minerals, such as silicate clays (e.g. smectitie, kaolinite, and mica), calcite, and gypsum. Laboratory techniques that measure silicate clay types include X-ray diffraction and X-ray fluorescence spectroscopy (Hiraoka, 1994). X-ray diffraction utilizes the scattering of X-ray beams as they hit a substance to determine the mineralogical makeup of a soil, while X-ray fluorescence uses high energy X-rays to cause the test sample to emit secondary (fluorescent) X-rays for the same purpose. Both methods require time intensive sample preparation, such as clay fractionation, saturation of exchange sites with a single cation, mounting, and several grams of a soil sample. Mineralogy is semi-quantitative where soil minerals are identified as being present and then categorized into relative quantity. VNIR spectroscopy can also categorize soils minerals. Brown et al. (2006) built a VNIR calibration for silicate clay minerals and was able to predict kaolinite and montmorillonite within one ordinal unit from X-ray diffraction data 96% and 88% of the time, respectively.

Organic substances in soils can also be useful in forensic soil science. In forensics, Zala (2007) deals with indentifying the unique mix of organic substances to identify a soil by examining the unique mementoes plants leave behind for soil characterization. Fourier Transform Infrared (FTIR) Spectroscopy is also being developed to isolate the spectral identity of a soil's organic compounds (Cox, 1999). Though VNIR spectroscopy is likely limited to its use of specifically identifying organic compounds in soils, it is currently used in many applications to measure organic carbon in soils, and classify organic compounds in herbivore manure. Wiedower et al., (2009) and Dittmar et al., (2006) use VNIR spectroscopy to identify animal forage quality by scanning feces. In this work specific proteins are identified, showing the potential of VNIR to be sensitive to various organic compound structures. Work to use VNIR spectroscopy to quantify organic carbon stocks in soils, has identified the spectral specificity of the method to carbon source (Christy, 2007; Kusomo et al 2008; Morgan et al, 2009).

Biological examination in forensic soil science has primarily focused on the presence and makeup of diatoms (unicellular organisms with species specific shells composed of silica (Goho, 2004)), opal phytoliths, and pollen. Different species of diatoms, pollen and microbial populations present in the soil can be used as to match commonalities between two soil samples.

Locard's Principle of Exchange states, every contact leaves a trace (Walls, 1974). This principle plays an important role in soil forensics. It implies that a suspect will leave evidence at a crime scene and more importantly, take evidence with him/her. Soil forensic scientists use this principle to tie soil evidence from a suspect to a crime scene. This thesis will focus on using VNIR spectroscopy to construct spectral fingerprints of different soils to aide in tying a suspect to a crime scene. The reason I chose to evaluate VNIR spectroscopy is that it is cost effective, supports rapid collection and analysis of data and most notably, is nondestructive. The fact that VNIR spectroscopy is nondestructive allows for further testing on trace amounts of soil evidence.

Hence, the *overall objective* of this thesis is to evaluate whether a VNIR spectral signature of a soil from a specific location is unique compared to the VNIR signatures of other soils. More specifically, we will test 1) the ability of VNIR spectral signatures to be differentiated between soil series and 2) characterize the variability of soil spectra from a specific location.

In chapter II of this thesis, the methodology employed to collect soil samples is described along with the subsequent statistical analysis of the data. There are a number of basic soil science terms that are used in the chapter on methodology, which are vital for understanding my research goals, and are briefly introduced here. First, a soil series is a classification within soil taxonomy. A series consist of soils that are similar in all major profile characteristics including color, texture, and structure. There are twelve soil textures based on United States Department of Agriculture classification (Sumner, 2000). A soil texture refers to a particle size category that includes pre-defined ranges in the percentages of sand, silt, and clay present within a soil (Brady, 2004); for example sand, loamy sand, silt loam, and clay loam to name a few. Though a single soil series is narrowly defined, the surface soil of a single soil series can differ in organic carbon content, carbonate content, and texture, among other things. The overall aim of this research is exploit these differences using VNIR spectroscopy, and to use this information to classify a soil that might be unique to a singular location, relative to other soils in the same series.

A mapping unit is a conceptual group of soils within a series that represent similar landscape areas delineated or identified by the same name in a soil survey (Brady, 2004). Like soil series, mapping units have characteristics that make them similar and different to other mapping units. Mapping units can be grouped based on texture, landscape position, and amount of weathering. Mapping units differ, like soil series but to a lesser degree (conceptually), in organic carbon content, clay content, and carbonate content.

# CHAPTER II

# METHODOLOGY

A crime scene location was selected at a Weswood soil series (Fine-silty, mixed, superactive, thermic Udifluventic Haplustept) in the Brazos River floodplain. An X-shaped design was constructed for the sample collection at the crime scene.
A sample was collected at 5-m increments for a distance 20 m, totaling four sample collection sites within each arm of the grid. A surface soil sample was collected to a depth of 10 cm with a width of 5 cm.

Additional soil-sampling locations were selected among four soil series, including Weswood. Two of the series were chosen because of their similarity in deposition and parent material to Weswood. The Ships (Very-fine, mixed, active, thermic Chromic Hapludert) and Yahola (Coarse-loamy, mixed, superactive, calcareous, thermic Udic Ustifluvent) are Holocene age alluvial materials, derived from mixed sources, found on 0-2 % slopes, and deposited by the Brazos River—like Weswood. The most important characteristic that unifies these three series is that all three are calcareous to the surface. The Yahola series is classified as an Entisol and is the most similar to the Weswood series. The Ships series differs in that it is a Vertisol, has a higher percentage of clay particles and has slickensides throughout its subsurface.

The fourth soil is Silawa (Fine-loamy, siliceous, semiactive, thermic Ultic Haplustalf). The Silawa series consists of very deep, moderately permeable well drained soils that formed in sandy and loamy sediments. This series is classified as an Alfisol and has a base saturation of less than 75 percent throughout the entire pedon.

Using the Soil Survey Database, provided by the National Resource Conservation Service (NRCS), 116 possible sampling locations were randomly selected, equally representing each of the four soil series. From the 116 sites, 48 were sampled. This selection was primarily based on public road access. Eight samples were collected from Ships, twelve from Yahola, and ten from Silawa, while sixteen samples were selected from Weswood.

In addition, several of the mapping units and series had different land uses, e.g. pasture, native vegetation, or agriculture. Change in land use is expected to alter the organic carbon signature in the soil VNIR spectrum. The collection of samples from different land uses will be used to determine how altering land use (i.e. organic carbon signature) changes the ability of VNIR to link and uniquely identify a soil sample associated with a specific crime scene.

At each of the 48 sampling locations and at each location at the crime scene, a total of three samples were collected in triangle geometry, approx 10 cm apart. Each sample was taken from the surface layer of soil (0 to 10 cm) using a tulip bulb planter (5 cm), air dried in an oven at 60$^{o}$C, and ground to pass through a 2-mm sieve. For scanning, 20 ml of soil was placed into a borosilicate glass Petri dish and scanned using an Analytical Spectral Devices AgriSpec VNIR spectroradiometer. This spectroradiometer has a spectral range of 350 to 2500 nm. Every sample was scanned twice, where the second scan was made after a 90 degree rotation of the Petri dish. After scanning, the collected spectra were processed by averaging the duplicate scans, taking the first derivative of the reflectance, and re-sampling the spectra at 10 nm intervals. The reflectance spectrum was also re-sampled to 10 nm waveband intervals. Processing the spectra averages to the first derivative of reflectance removes albedo effects and some effect of non homogeneity of particle size.

Two statistical tools were used to explore the reflectance and first derivative of reflectance spectra, Principle Component Analysis (PCA) and Linear Discriminate Analysis (LDA). These techniques were be used to summarize the uniqueness of the soil spectra within each soil series, within each mapping unit and to see examine the uniqueness of the soil spectra from the crime scene.

Transforming multi-dimensional data, like spectra data, into principle components is a way to reduce the information in highly dimensional data to a manageable number of dimensions that can be visualized and analyzed (Webster, 2001). Generally, PCA allows us to visualize the structure of spectral data especially view that structure with respect to other spectral data (Webster 2001). In this application the multi-dimensional data analyzed are the spectral reflectance and first derivative of spectral reflectance of various soil samples. All PCA analysis was performed in R using the prcomp function, with variances scaled to a unit variance and variables shifted to be centered at zero (R Development Core Team, 2004).

To categorically classify soil spectra using VNIR spectroscopy, LDA was used to directly classify soil spectra into soil series and finally classify the crime scene soils. To initially evaluate the potential of LDA, principal component plots were created to visually assess the spectral distinctness between each series and between the crime scene and the 48 soil samples representing a larger population (Islam et al., 2005). For LDA analysis the first seven PC's, were selected because they explained 76.5 % of the spectral variability. Using the lda function in R, the soil series and the crime scene were classified. For LDA training, one set of training data were used. The training set was a random selection of two thirds of all the soil spectra. Once the model was trained, the remaining one third of the soil spectra was classified into soil series and as being part of the crime scene.

# CHAPTER III

# RESULTS

Soil reflectance data averaged by soil series and by crime scene show the overall spectral fingerprint of soil series (Fig. 1). Because Silawa is a non calcareous terrace soil its signature is different from the floodplain soils. Additionally, it is not surprising that the spectral reflectance of Ships is also different from Yahola and Weswood because Ships surface texture is higher in clay content. The similarity between reflectance of Yahola and Weswood soils was also expected because Weswood and Yahola are usually found in near proximity to each other and could therefore be easily misclassified at the soil survey mapping resolution. The soil surface of Yahola and Weswood are very similar in texture, fine sandy loam and silt loam respectively. Because the crime scene samples were mapped as Weswood, it is surprising that these reflectance values are so different, on average, from the Weswood reflectance values. Of course, reflectance includes albedo effects and albedo is highly dependent on soil organic matter. Hence an increase or decrease in soil organic matter from change in land use can significantly affect albedo within an individual soil series.

The spectral range, which shows the most differentiation between the soil series samples and the crime scene samples, is from 1500-2500 nm (Fig. 1). In this range, the Weswood and Yahola samples have separated from one another more significantly, with the greatest separation at around 2250 nm. The separation of the Weswood and Yahola might be due to varying amounts of calcite or calcium carbonate in the soil. Using continuum removal, Lagacherie et al. (2007) used spectral reflectance at 2340 nm to quantify calcium carbonate of 52 soil samples. And Morgan et al. (2009) showed PLS predictions of calcium carbonate in soils being associated with nine wavebands, seven of them included 2300, 2330-2350, 2370-2380, and 2490 nm.

The next processing step is to take the first derivative of the reflectance. In prior studies, the first derivative of reflectance has more predictive power for soil properites than reflectance because it removes extraneous spectral effect due to hetergenous aggregate size, variable moisture, and other albedo effects (Waiser et al., 2007; Morgan et al., 2009). Figure 2 shows the first derivative of reflectance averaged for each soil series and the crime scene. The first derivative amplifies spectral absorbences seen as dips in the reflectance plot, specifically at 250, 1000, 1900 and 2200. In Figure 2, we see a large amount of overlap between all the samples and it is difficult to differentiate series from one another as well as from the crime scene data. The crime scene data appear most different at 500, 1000, and 2200 nm. As in Figure 1, the wavelength range that most differentiates the soil series from one another and the crime scene is the 1500-2500 nm range.

Principle components plots were used for three purposes. First, PCA was used to choose between reflectance data or first derivative of reflectance for subsequent analysis. Secondly, PCA was used to visualize whether the spectral data obtained from soil samples can be used to differentiate the different soil series from one another and primarily differentiate the crime scene soil samples from the other soil series samples. Lastly, we used PCA to determine how many principle components to use in the LDA classification.

To decide on whether or not to transform the data (first derivative); the principle component (PC) decomposition was plotted for the first four PCs for both the reflectance and first derivative. Visually, the level of clustering by was assessed. Figure 3 shows the results of the PC analysis of the reflectance for the soil series (red, green, and blues) and the crime scene (black) samples. No distinct clustering or aggregation of individual colors (soils) is apparent. However, the crime scene samples are tightly clustered together indicating some level of uniqueness and spectral similarity among each other. Figure 4 plots the first four PCs of the first derivative of the reflectance. Within the PC plot of the first derivative there appears to be more distinct clustering among each soil series and the crime scene compared to the PC plot of reflectance. For example, in the quadrat that represents PC1 vs. PC4 the aqua colored Ships soils are more closely grouped in Fig. 4 as well as the red colored Silawa samples. Based on this assessment, the first derivative of the reflectance was assumed more capable of clustering the soil series and the crime scene samples. Therefore subsequent analysis was performed on the first derivative of the reflectance only.

The PC plot in Fig. 5 is similar to Fig. 4 except all samples not belonging to the crime scene are colored pink. This plot more clearly illustrates shows the unique clustering of the crime scene samples from all other samples collected. However, in this PC plot there does appear to be some overlap of the crime scene samples and the series samples. Figure 6 is a plot of PC1 vs. PC2 of the first derivative of the reflectance. If a polygon (or convex hull) was drawn around the outer edges of the crime scene, no other samples would fall within the polygon. However, soil spectra that are close to the crime scene spectra include identification numbers 3, 6, 26, and 40, which are classified as Weswood or Yahola soils. The close proximity of these four samples is not unexpected because the crime scene is mapped as Weswood, and as stated earlier, Yahola is often mapped in close proximity with Weswood due to its similar geographical location.

Lastly, Linear Discriminant Analysis (LDA) using the principle component decomposition was used to classify a random subset of the soil series and crime scene dataset. The first seven principle components were used for classification as they described 76 % of the variance in the spectra. The LDA classification trained on a random subset of two thirds of the samples, using the first derivative of the reflectance.

Table 3 shows the results of LDA classification of the validation dataset (n=13). If LDA had correctly classified all of the spectra, all of the numerical values would have been in the highlighted diagonal line and zeros would be elsewhere. LDA correctly classified eight (62 %) of the soil series spectra into the correct soil series and eight (89 %) of the crime scene spectra. Of the misclassified spectra, 83 % were wrongly classified as Ships.

Overall, the PCA and LDA analysis of the first derivative of reflectance moderately differentiated the soil series from one another. A couple of possibilities for misclassification of soil series exist. For one, clustering of the spectral data was weak because some of the samples were very similar, spectrally. An example of this type of error is the inability of spectroscopy to differentiate between Yahola and Weswood. A second and potentially more likely reason for misclassification in LDA could be that the soils that are labeled as belonging to one series actually do not. The USDA soil survey is mapped at a 1:24000 scale and for any given soil mapping unit polygon in that survey there can be up to 10% exclusions of different soils. We used the Soil Survey map to identify the presence of, and collect a soil at the cm-scale. To eliminate this source of error, laboratory measurement of particle size distribution is needed to verify the correct classification of the soil samples. Lastly, land use could also be confounding the LDA classification. A Yahola soil and a Ships soil with similar land use will have a similar organic matter signature. The next step in this work is to specifically address the misclassification and look at the effect of land use.

# CHAPTER IV

# CONCLUSION

The results of this study show that VNIR spectroscopy has some utility in identifying unique spectral signatures of soils for the use in forensic soil science. The first derivative of the reflectance proved to be more useful than the reflectance for PCA and LDA, agreeing with many other investigations in soil spectroscopy (Brown et al., 2005; Brown et al., 2006; Waiser et al., 2007; Morgan et al., 2009). Particularly LDA shows promise as a method for classifying the soils. Further work on laboratory analysis is needed to determine if the initial classification of the soil samples collected from the four series was correct. Additional LDA and PCA analysis might elucidate the contribution of land use to better or worse classification.

For the classification of the crime scene samples, both PCA and LDA more precisely differentiated the crime scene spectra from the spectral data of the soil series. In conclusion VNIR spectroscopy with further evaluation of this data set and looking at a larger spectral library will be applicable in forensic situations.

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# APPENDIX

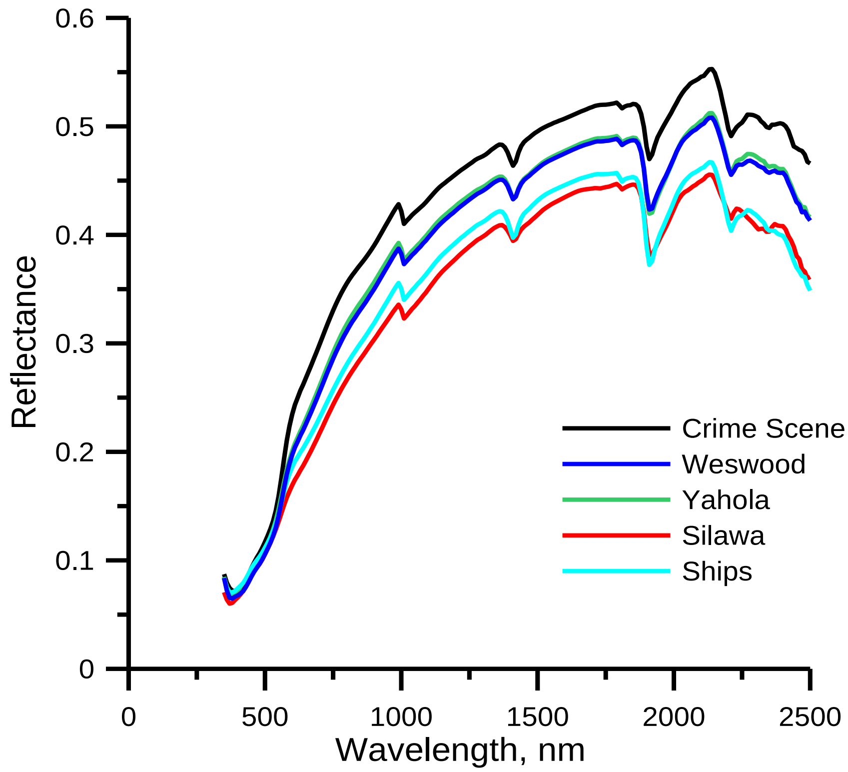


**Figure 1.** Averages of reflectance for each soil series and the crime scene.

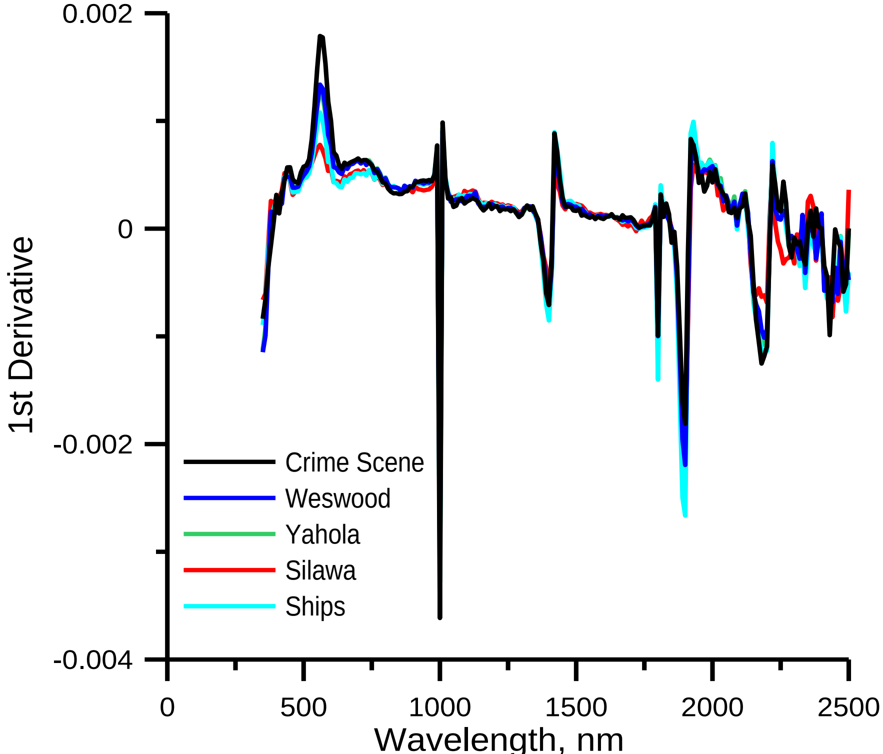


**Figure 2.** Averages of the 1st derivative of reflectance for each soil series and the crime scene

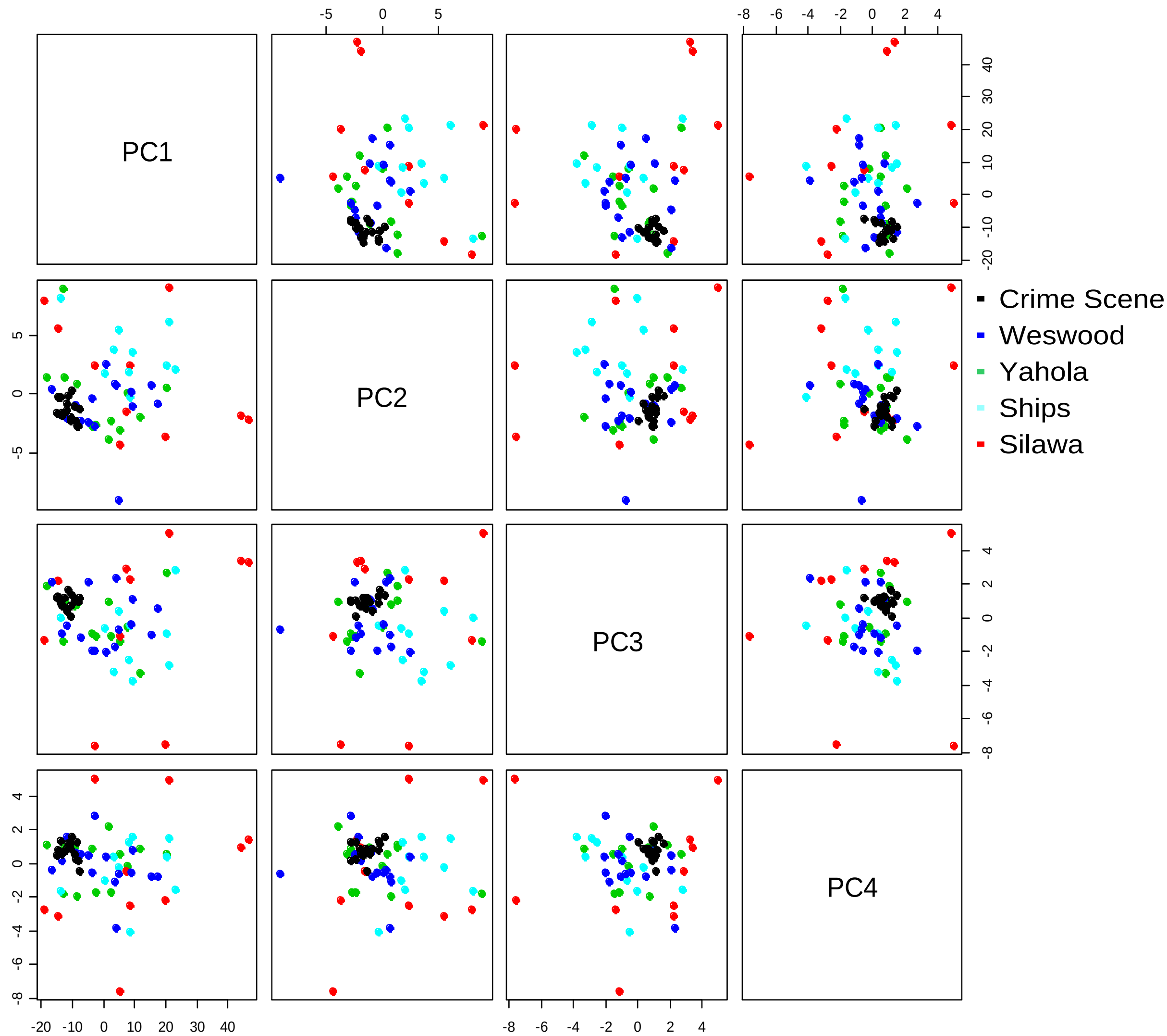


**Figure 3.** A principal component (PC) plot is shown for the first four PCs of the reflectance. Each color represents a soil series and black is the crime scene (mapped as Weswood). Dark blue is Weswood; aqua is Ships; red is Silawa; green is Yahola.

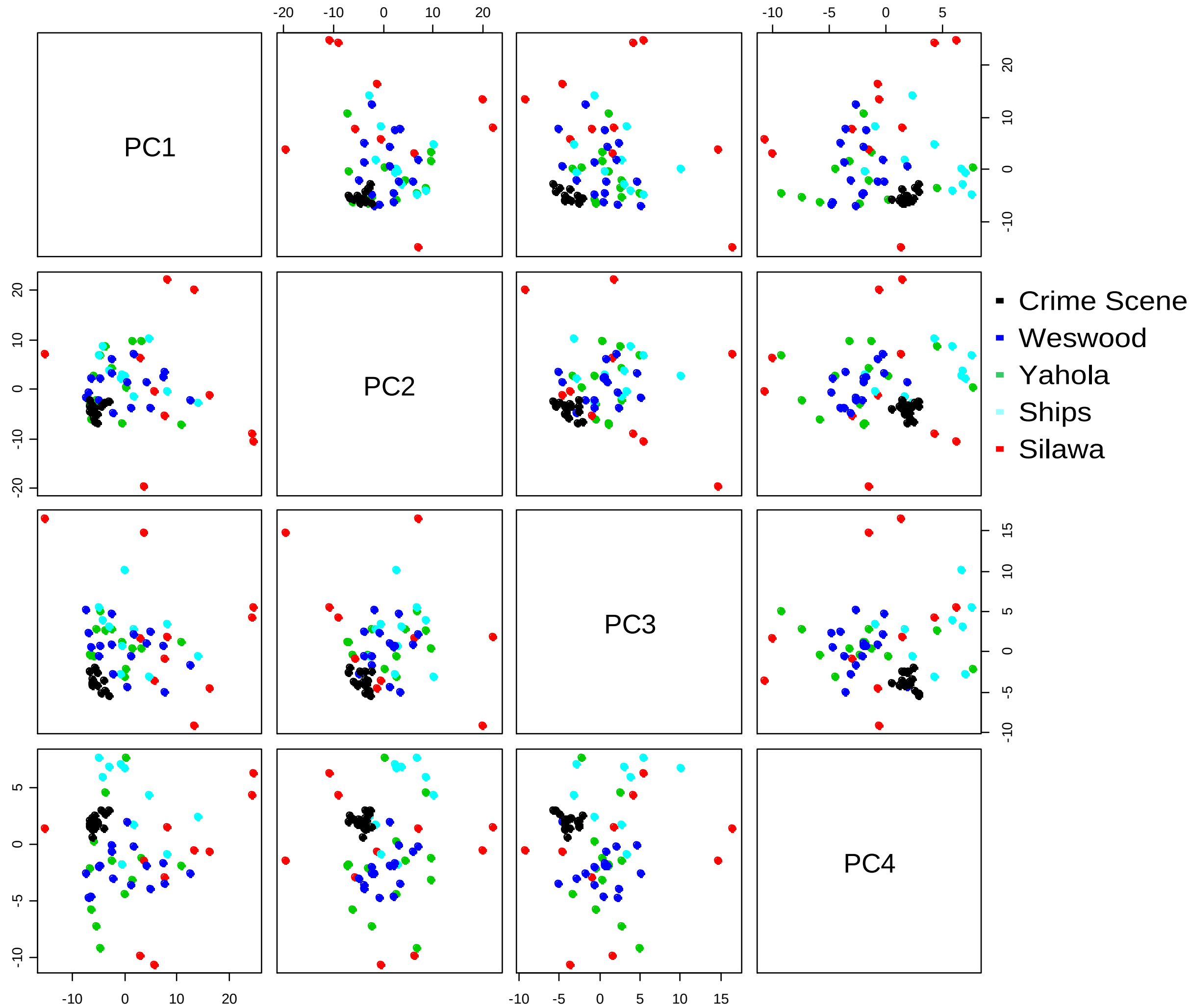


**Figure 4.** A principal component (PC) plot is shown for the first four PCs of the first derivative of reflectance. Each color represents a soil series and black is the crime scene (mapped as Weswood). Dark blue is Weswood; aqua is Ships; red is Silawa; green is Yahola.

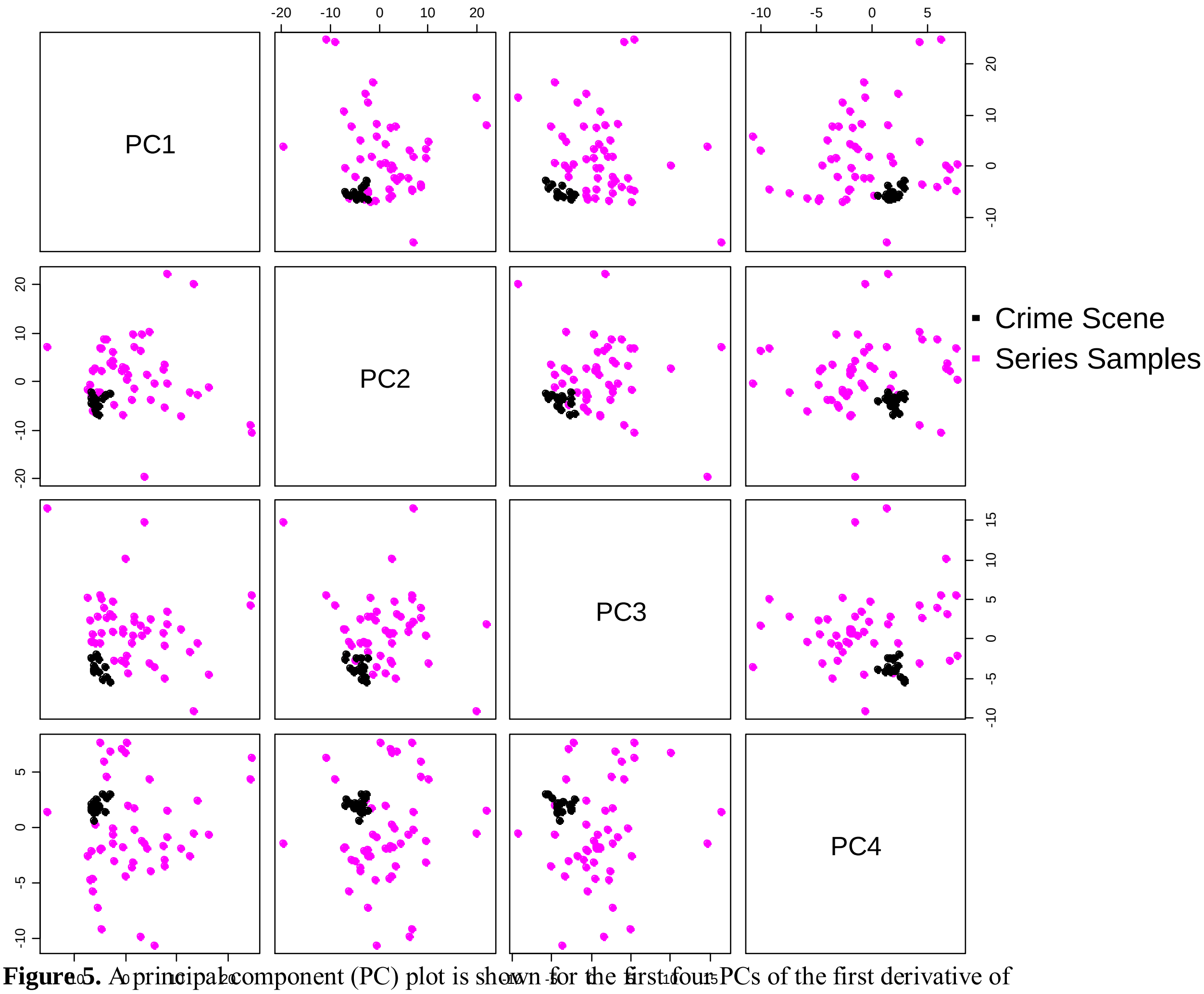


**Figure 5.** A principal component (PC) plot is shown for the first four PCs of the first derivative of reflectance. The pink color represents all the soil series samples and black is the crime scene (mapped as Weswood).

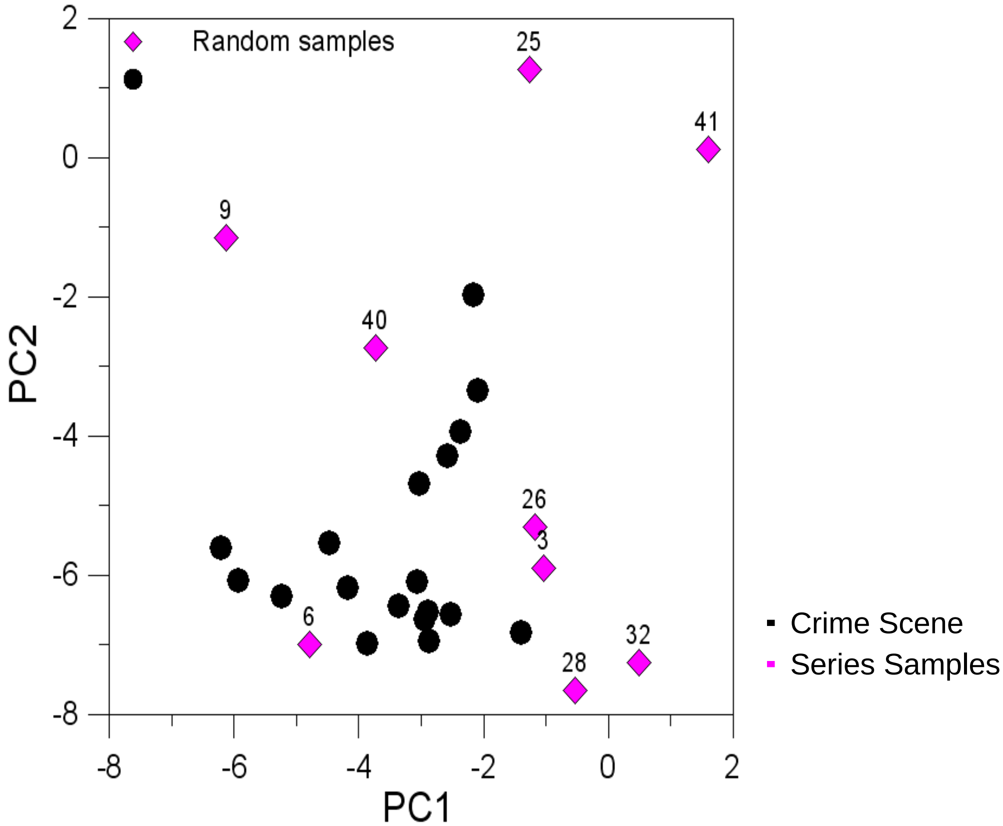


**Figure 6.** A single principal component (PC) plot of PC1 vs. PC2 the first derivative of reflectance. The pink color represents all the soil series samples and black is the crime scene (mapped as Weswood)

**Table 1.** Selected mapping units of the different series.

| Series | Mapping unit | Original | Samp-led |
|---|---|---|---|
| | | --number-- | |
| Weswood | Weswood silt loam, 0-1% slope, rarely flooded | 24 | 4 |
| | Weswood silt loam, 1-5% slope, rarely flooded | 5 | 4 |
| | Weswood silty clay loam, 0-1% slope, rarely flooded | 29 | 4 |
| | Weswood silty clay loam, 1-3% slope, rarely flooded | 9 | 4 |
| Yahola | Yahola loam, occasionally flooded | 3 | 0 |
| | Yahola fine sandy loam, 0-2% slope, rarely flooded | 28 | 12 |
| Ships | Ships clay, 0-1% slope, rarely flooded | 3 | 4 |
| | Ships clay, 1-3% slope, rarely flooded | 5 | 2 |
| | Ships clay, 0-1% slope, frequently flooded | 2 | 1 |
| | Ships clay, rarely flooded | 3 | 3 |
| Silawa | Silawa loamy fine sand, 1-5% slope | 2 | 2 |
| | Silawa fine sandy loam, 2-5% slope | 6 | 5 |
| | Silawa fine sandy loam, 5-8% slope | 4 | 1 |
| | Silawa loamy fine sand, 1-3% slope | 3 | 2 |

**Table 2.** Land use within each soil series.

| Series | Land use | Number collected |
| --- | --- | --- |
| Weswood | Agriculture | 12 |
| | Pasture | 3 |
| | Native | 1 |
| | Residential | 0 |
| Yahola | Agriculture | 8 |
| | Pasture | 1 |
| | Native | 3 |
| | Residential | 0 |
| Ships | Agriculture | 2 |
| | Pasture | 3 |
| | Native | 3 |
| | Residential | 0 |
| Silawa | Agriculture | 0 |
| | Pasture | 2 |
| | Native | 6 |
| | Residential | 2 |

**Table 3.** Classification results from Linear Discriminate Analysis of the first derivative of the reflectance for all soil series and the crime scene.

| | | Actual Series | | | | |
|---|---|---|---|---|---|---|
| | | Yahola | Silawa | Ships | Wes-wood | Crime Scene |
| LDA Predicted Series | Yahola | 2 | 0 | 0 | 1 | 0 |
| | Silawa | 0 | 2 | 0 | 0 | 0 |
| | Ships | 2 | 1 | 1 | 1 | 1 |
| | Weswood | 0 | 0 | 0 | 3 | 0 |
| | Crime scene | 0 | 0 | 0 | 0 | 8 |

# CONTACT INFORMATION


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